Toolink: Linking Toolkit Creation and Using through Chain-of-Solving on Open-Source Model

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Abstract

Large Language Models (LLMs) have demonstrated remarkable progress in utilizing tools, but their closed-source nature and high inference costs pose limitations on their adaptability, necessitating a valid method that leverages smaller, open-sourced models. In this paper, we introduce Toolink, a comprehensive framework that performs task-solving by first creating a toolkit and then integrating the planning and calling of tools through a chain-of-solving (CoS) approach. We first validate the efficacy of Toolink in harnessing the model's creativity and CoS ability on ChatGPT. Subsequently, we curate CoS-GPT, a chain-of-solving dataset designed for tool-using, and finetune the LLaMA-7B model. It results in LLaMA-CoS, a powerful open-source model with advanced tool-planning and tool-calling capabilities. Evaluation of diverse tasks from BIG-bench demonstrates its CoS ability matches that of ChatGPT while its performance surpasses the chain-of-thought approach. Further studies highlight the generalization of LLaMA-CoS to unseen tasks and showcase its capability in using toolkits not explicitly tailored for the target task, affirming its robustness in real-world scenarios. All codes and data are released[1].

1 Introduction

Large Language Models (LLMs) such as Codex (Chen et al., 2021), ChatGPT (OpenAI, 2022), and GPT4 (OpenAI, 2023) have made significant strides in code generation, in-context learning, and logical reasoning. However, they still struggle with precise calculations and accessing current information (Patel et al., 2021; Trivedi et al., 2022; Lu et al., 2022b). To address these issues, research has focused on equipping LLMs with tools such as calculators (Cobbe et al., 2021; Parisi et al., 2022; Schick et al., 2023), search engines (Carlini et al., 2021; Thoppilan et al.,
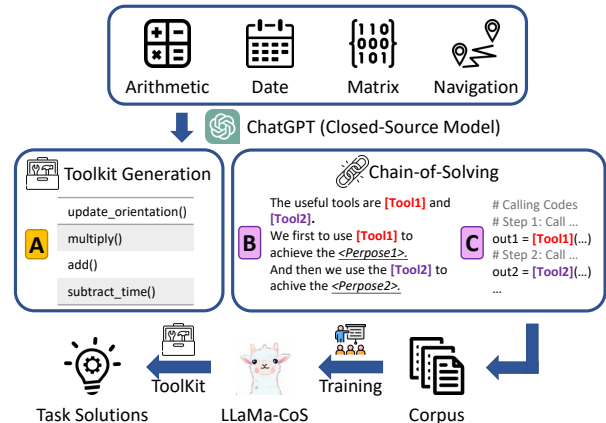

Figure 1: An illustration of Toolink, which decomposes tasks via toolkit creation and resolves queries through Chain-of-Solving (CoS). Toolink can be adapted to open-source LLaMA for enhanced tool usage.

2022; Schick et al., 2023), scratch pads (Nye et al., 2021), calendars (Schick et al., 2023), and image retrievers (Sheynin et al., 2022) to enhance their capabilities, thus benefiting various tasks including question-answering, math calculations, and long-form generation. Recent studies have also explored how LLMs can devise plans, make decisions, and perform tool invocations (Shen et al., 2023; Lu et al., 2023; Liang et al., 2023). By combining them into a pipeline, these frameworks aim to construct more advanced NLP systems for improved task performance.

However, current tool-using pipelines heavily rely on closed-source models with inaccessible parameters. It poses challenges particularly as follows: i) **Limited adaptability**: The closed-source nature of major LLMs prevents them from customization, resulting in a lack of flexibility to adapt to tasks with specific requirements. ii) **Low efficiency and high inference cost**: Many existing LLMs can only be accessed *online*, which imposes limitations on the inference rate and leads to high expense. iii) **Privacy and security concerns**: Each

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[1]https://github.com/qiancheng0/Toolink

query must be submitted to these closed-source LLMs to obtain a tool-using solution, which raises concerns regarding potential privacy breaches and compromises data security.

To address these challenges, we propose Toolink, a comprehensive framework to boost the tool-using ability of open-source models with the help of closed-source models. As shown in Figure 1, Toolink first decomposes the target task by creating a toolkit for problem-solving, and then leverages the open-source model to use tools to answer queries in a chain-of-solving (CoS) approach. Specifically, CoS disentangles the model's reasoning through two stages: *CoS-Planning*, which selects useful tools from the created toolkit and plans their usages based on the specific query; and *CoS-Calling*, which focuses on deriving the answer by performing tool invocations in code format according to the plan devised. To effectively train the open-source model in these abilities, we employ ChatGPT to curate CoS-GPT, a training dataset that aims to inspire the tool-using ability of open-source models through CoS. Specifically, we finetune LLaMA-7B (Touvron et al., 2023) into LLaMA-CoS, which is equipped with strong tool-using capabilities by linking toolkit creation with the chain of problem-solving.

LLaMA-CoS can solve the queries *offline* without uploading queries to closed-source models, ensuring data security and privacy. Experiments further illustrate that Toolink outperforms the chain-of-thought (CoT) (Wei et al., 2022) on diverse tasks from BIG-bench (Srivastava et al., 2022) and enables LLaMA-CoS to showcase comparable CoS ability to that of ChatGPT. In addition, LLaMA-CoS can generalize to unseen tasks by planning and calling tailored tools, and solve the target task with a toolkit not specifically tailored for it. These findings further affirm our framework's robustness in solving queries under real-world scenarios.

2 Related Work

Tool-based enhancement for LLMs. Language models have been enhanced with external tools to improve their expertise. Previous work focused on equipping the LLMs with different tools including a calculator to improve calculation accuracy (Cobbe et al., 2021; Parisi et al., 2022; Schick et al., 2023), search engine to inquire factual knowledge (Carlini et al., 2021; Thoppilan et al., 2022; Schick et al., 2023), Python interpreter to execute

programs (Chen et al., 2022a; Gao et al., 2022), and retriever to search textual information (Khandelwal et al.; Borgeaud et al., 2022), etc.

More recent studies, such as HuggingGPT (Shen et al., 2023), Chameleon-LLM (Lu et al., 2023), VisualGPT (Wu et al., 2023) and TaskMatrix.AI (Liang et al., 2023), focus on assembling plannings, execution, and reasoning about tools into a robust pipeline. In addition to tool-using, ART (Paranjape et al., 2023) builds toolkits based on retrieved tasks from the manually built library, while LATM (Cai et al., 2023) and CREATOR (Qian et al., 2023) involve the LLMs' tool-making ability to offload their reasoning burden and raise task performance. In contrast to their prevalent use of closed-source LLMs to leverage tools, Toolink offers unique advantages of tool use for smaller, open-source models.

Adaptation of open-source models. One research direction focuses on effective tuning of open-source models, including the introduction of lightweight modules such as Adapter (Houlsby et al., 2019) and LoRA (Hu et al., 2021). These modules are adapted to various model types including LLaMA (Touvron et al., 2023), T5 (Raffel et al., 2020), and other Transformers-based architectures (Pfeiffer et al., 2020), to save computational resources. For instance, GOAT (Liu and Low, 2023) applies LoRA to improve LLaMA's arithmetic calculation ability, while LLaMA-Adapter (Zhang et al., 2023) adopts Adapter and zero-init attention to improve multi-modal task performance.

Other works have investigated how instruction tuning can make open-source models better understand and follow human requirements in both text format (Longpre et al., 2023; Ouyang et al., 2022) and visual domains (Liu et al., 2023). More recent works also investigate the curation of instruction following data (Taori et al., 2023; Peng et al., 2023) and construction of open-source tool-using agents (Qin et al., 2023; Zeng et al., 2023). Toolink builds upon the instruction-following paradigm and focuses on tool-using ability through the disentanglement of CoS-Planning and CoS-Calling, which makes learning more efficient.

3 Toolink Framework

As shown in Figure 2, Toolink first adopts toolkit creation to break down the target task through generating potential tools for task-solving (§ 3.1).
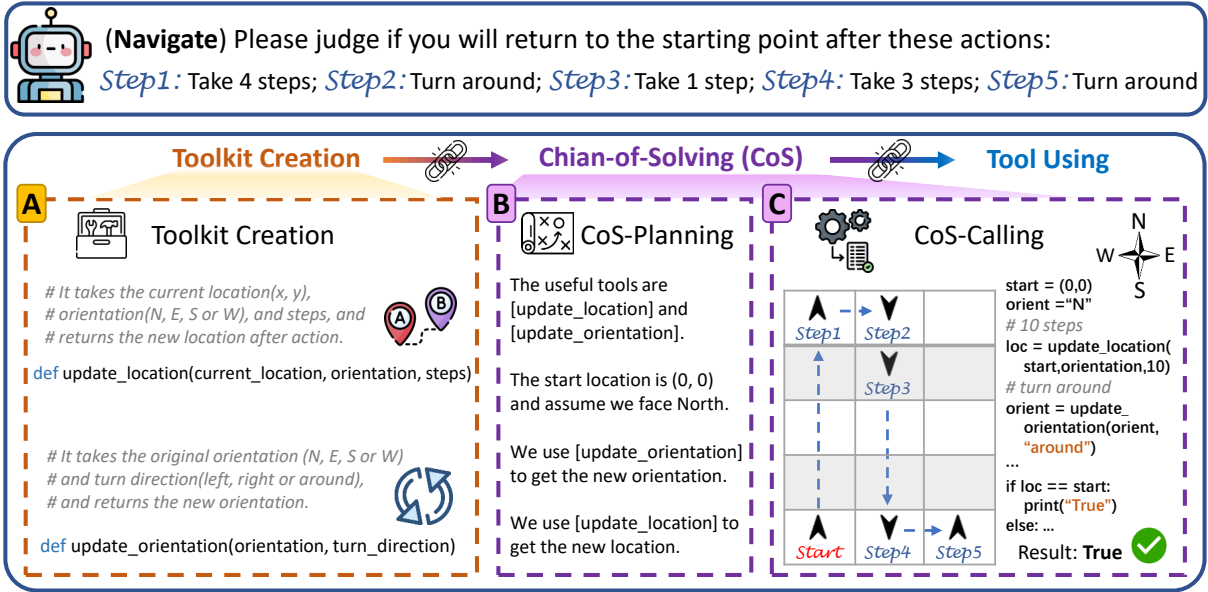
Figure 2: A problem solving chain of Toolink pipeline. We show an example from task Navigate. Toolink first creates a toolkit generally applicable to the task, and then approaches the specific query through CoS, which involves planning and calling of the created tools.

Then, the model links these created tools to address specific queries by selecting pertinent tools from the toolkit, planning their uses, and performing tool invocations (§ 3.2). This new reasoning approach, referred to as chain-of-solving (CoS), not only enables the effective and coherent application of tools but also facilitates the tool-using adaptation on the open-source model (§ 3.3).

3.1 Toolkit Creation

Toolkit creation decomposes a general task into modular and essential tools for problem-solving, facilitating more flexible tool utilization.

Overview. Given the target task T, toolkit creation breaks it down into more manageable components $t_1, t_2, ..., t_n$ through generating a toolkit $K_T = \{k_1, k_2, ..., k_n\}$, where $k_i (i \leq n)$ represents the tool to solve the subtask t_i. We illustrate our approach in Figure 2A, where the target task $T = \texttt{Navigate}$ is decomposed into t_1 (movement in a single direction) and t_2 (change of orientation). Each component is represented by a specific implementation encapsulated within a function tool.

Toolkit Making. We utilize ChatGPT for task decomposition. For each task T, we provide Chat-GPT with a task description and a few data samples $D_{T\text{-sample}}$, expecting them to facilitate the model's understanding of task T's objective and identify commonalities among queries. The prompting de-

tails are presented in Appendix A and Figure 6. Note that our design requires only a few data points as demonstrations fed into the closed-source Chat-GPT, leaving the entire testing set for local processing to maintain privacy.

Tool Details. Each tool k_i within the toolkit K_T is comprised of a concise introduction and its corresponding code implementation. The introduction provides a brief overview of k_i's utility, inputs, and outputs, facilitating effective planning and calling in subsequent steps.

3.2 Chain-of-Solving

Chain-of-solving (CoS) involves deliberate planning and decision-making for tool invocation, which bridges the gap between toolkit creation and downstream tool use for task query resolution. CoS is disentangled into CoS-Planning and CoS-Calling. This separation allows for a more transparent and interpretable reasoning path, thereby enhancing the applicability of CoS to open-source models.

CoS-Planing. The CoS-Planning stage entails selecting useful tools from a toolkit K_T in response to a specific query of task T. It employs natural language-based reasoning chains, referred to as a *plan*, to determine the most effective way to utilize the selected tools to solve the given query.

In Figure 2B, the model devises strategies for employing tools to update the location and orien-

Category	Set Name	Source	Number
Tool-Using	Tool-Planning	Augmented	4.4K
	Tool-Calling	Augmented	4.4K
Code Generation	Python-Simple	New	2.0K
	Python-Specific	New	2.0K
	Math	Augmented	2.5K
	Algorithm	Github	2.3K
	LeetCode	LeetCode	0.8K
	Rectification	Sources Above	1.6K
Total	-	-	20.0K

Table 1: The statistics about the sources and number of data points in each category of CoS-GPT. *Augmented* represents augmented from an existing dataset.

Category	Task Name
Mathematics	Arithmetic, Matrix Shape, Chinese Remainder
Common Sense	Date Understanding, Navigate
Logical Reasoning	Dyck Language, Boolean Expression
Decomposition	Tracking Shuffled Objects

Table 2: The categories of 8 BIG-bench tasks tested.

tation, with additional initial conditions that serve as a guiding hint. Planning plays a crucial role in establishing a link between toolkit creation and decision-making, thus reducing the cognitive burden associated with tool-use reasoning.

CoS-Calling. The CoS-Calling stage entails the utilization of selected tools and interpretation of the plan into program language to perform tool calls. The plan generated in the previous stage serves as the guidance for program implementation. During the tool execution, all results from the tool invocations are implicitly captured and used to extract the final answer for the given query.

Figure 2C illustrates this process, where the model simulates the entire navigation process using code as the underlying medium. In this example, the model derives the final correct answer, thereby demonstrating a successful CoS-Calling process.

3.3 Open-Source Model Adaptation

Considering the limited adaptability, high inference cost, and privacy concerns posed by closed-source models, we aim to enhance the CoS ability in open-source models. We propose the CoS-GPT, a specialized training dataset that emphasizes the planning and calling of tools, along with code generation. These elements are crucial for boosting the model's CoS ability. The statistics related to CoS-GPT are presented in Table 1. Furthermore, for each specific target task T, we employ $D_{T\text{-sample}}$ to generate a task-specific dataset. This is achieved by augmenting each sample query with suitable tools, thereby facilitating a more effective training of task T on the open-source models.

Construction of CoS-GPT. To enhance the open-source model's skills in applying tools for problem-solving, we construct CoS-GPT from scratch to improve the model's CoS ability from planning, calling, and coding. We include the first two aspects as they are essential for CoS within Toolink, and the last aspect as it serves as the medium for tool-using.

For data points about planning and calling, we enhance the AQUA-RAT (Ling et al., 2017), GSM8K (Cobbe et al., 2021), and TabMWP (Lu et al., 2022a) datasets, comprising graduate-level math problems, numerical reasoning tasks, and diverse table contents, with toolkits. Each query is augmented with a toolkit containing both useful and redundant tools. The model's objective for planning is to select and plan the use of useful tools, while for calling, the objective is to learn how to call the chosen tools through codes. We apply ChatGPT to simulate this process and utilize their responses for dataset construction. Please refer to Appendix E.1 for more details.

Data points for code generation encompass diverse sources, including augmentation from existing datasets, GitHub repositories, and newly generated data, detailed in Appendix E.2. Each query adheres to an instruction-following pattern and aims to enhance the open-source model's understanding of code while expanding its versatility in making informed decisions when performing CoS.

Construction of Task-Specific Data. For each target task T, we construct 200 tool-augmented data points (100 each for plan and call) from the publicly available samples $D_{T\text{-sample}}$, and use them to tune the open-source model together with CoS-GPT. Similar to the construction process for tool-using data in CoS-GPT, we first augment T with a toolkit K_T. Next, we employ ChatGPT to select useful tools for each query and generate the calling decision. The decision's output is compared against the standard answer, and minor adjustments may be made to ensure the augmented data's validity.

Open-Source Model Finetuning. Together with CoS-GPT, we apply the tool-augmented data points

from all target tasks to finetune the open-source model. We expect the derived tool-augmented open-source model to excel in applying useful tools for problem-solving. By planning and calling through CoS, this model links the created toolkit with specific queries, which realizes the final goal of the Toolink framework.

4 Experiments

To evaluate the effectiveness of Toolink, we first conduct a validation test using ChatGPT. We select eight distinct tasks from the BIG-bench dataset (Srivastava et al., 2022) to investigate whether Toolink can effectively leverage ChatGPT's creativity and tool-using capability to improve task performance.

Subsequently, we finetune the open-source LLaMA-7B model following the adaptation process outlined in § 3.3. This results in LLaMA-CoS, a model capable of linking the created toolkit with specific tool use through CoS. We evaluate the effectiveness of LLaMA-CoS in utilizing tools on the same set of eight tasks and showcase its excellence.

4.1 Validation Evaluation

Settings. To evaluate the effectiveness of Toolink, we conducted a validation test using ChatGPT on eight tasks of diverse categories from BIG-bench, as detailed in Table 2. For each task, we first employ ChatGPT to create a toolkit, outlined in § 3.1. The total number of tools in the toolkit created for each task is shown in Table 3, with the tool's implementation details provided in Appendix B. Equipped with these tools, ChatGPT is presented with instructions and demonstration examples to perform CoS for problem-solving, detailed in Appendix C.

Baselines. We compare CoS against two baselines: i) **Vanilla** baseline, where ChatGPT directly produces the final answer. ii) **CoT** baseline (Wei et al., 2022), where ChatGPT performs chain-of-thought reasoning before providing an answer.

Evaluations. We evaluate the ability of ChatGPT to leverage plans and calls to perform CoS. The accuracy is measured by matching the model's final output to the correct answer. In addition, we also evaluated the individual contributions of CoS-Planning and CoS-Calling separately.

During CoS-Planning, the model is asked to select useful tools and plan their uses given the created toolkit. The planning accuracy is thus mea-

sured by the following metric:

$$ACC = \max\{\frac{|K_{\text{correct}}| - |K_{\text{error}}|}{|K_{\text{correct}}| + |K_{\text{error}}|}, 0\}, \quad (1)$$

where $|K_{\text{correct}}|$ denotes the number of correct (useful) tools in the toolkit selected in the model's generated plan, while $|K_{\text{error}}|$ denotes the number of incorrect (redundant) tools selected.

During CoS-Calling, the model is asked to implement the plan using code as the medium, after the useful tools are selected. The accuracy is thus measured by matching the output from the final execution with the correct answer. Please refer to Appendix D for more details regarding the separated test of CoS-Planning and CoS-Calling.

Results. The results are presented in Table 3. ChatGPT which uses tools through the CoS approach achieves significantly improved performance compared to other baselines, with notable margins of superiority. Further, the accuracy for CoS-Calling and CoS-Planning individually is even higher, indicating successful reasoning in each step of CoS which links toolkit creation with specific uses. These findings affirm the validity of Toolink, establishing a strong basis for its potential transferability to smaller, open-sourced models.

4.2 Experiments on LLaMA-CoS

Our primary objective is to apply Toolink to smaller, open-sourced models. To this end, the models from the LLaMA family (Touvron et al., 2023) stand out due to their capability to perform reasoning and generate codes. Considering the affordability of computational resources, we select LLaMA-7B as the representative base model to evaluate the performance of Toolink on open-source models.

Obtaining LLaMA-CoS. We follow the adaptation process outlined in § 3.3 and finetune LLaMA-7B with CoS-GPT and eight sets of task-specific tool-augmented data. The eight tasks are the same ones as those we test in § 4.1. Applying the training setting detailed in Appendix F, we derive a powerful variant, LLaMA-CoS, that excels in using tools through CoS.

Settings. We use LLaMA-CoS as the representative finetuned open-source model for testing. Building upon the validation test conducted on ChatGPT, we evaluate LLaMA-CoS's performance on the same set of eight tasks from BIG-bench. We keep all the metrics the same as in § 4.1

Task	Arith.	Date U.	Matrix S.	Navigate	Chinese R.	Dyck L.	Boolean E.	Tracking S.	Average
Num. of Tools	5	3	5	2	2	4	2	4	3.38
Vanilla	77.78	68.67	40.90	65.16	0.0	19.40	80.70	23.67	47.03
CoT	79.44	68.67	80.46	87.96	0.0	19.42	75.88	40.78	56.58
CoS	100.00	69.28	93.67	85.30	95.14	52.46	97.37	99.11	**86.54**
CoS-Planning	100.00	66.16	95.18	94.78	100.00	74.58	95.39	99.85	90.74
CoS-Calling	100.00	90.96	97.44	88.44	95.67	98.55	93.42	100.00	95.56

Table 3: We record the number of tools in the toolkit created for each task and demonstrate the accuracy (%) of ChatGPT on 8 BIG-bench tasks under different settings. We report the results of Vanilla, CoT baselines, and our CoS method, and report the performance of CoS-Planning and CoS-Calling separately.

Method	Model	Arith.	Date U.	Matrix S.	Navigate	Chinese R.	Dyck L.	Boolean E.	Tracking S.
CoT	Alpaca	19.89	39.76	5.62	47.11	0.0	0.0	57.46	0.44
(*Prompting*	LLaMA-7B	39.44	33.73	12.58	39.70	0.0	2.90	50.44	14.22
w/ demo)	ChatGPT	79.44	68.67	80.46	87.96	0.0	19.42	75.88	40.78
CoT (*Tuned*)	LLaMA-CoT	50.44	49.40	70.82	71.64	0.0	35.27	62.72	28.44
CoS	Alpaca	17.78	7.83	3.00	48.60	7.56	1.00	94.74	6.78
(*Prompting*	LLaMA-7B	55.89	17.47	10.65	45.90	23.80	35.83	99.12	0.67
w/ demo)	ChatGPT	**100.00**	69.28	**93.67**	85.30	95.14	52.46	97.37	99.11
CoS (*Tuned*)	LLaMA-CoS	**100.00**	**74.10**	91.01	**99.56**	**95.44**	**98.21**	**100.00**	**99.56**

Table 4: The accuracy (%) of baselines and LLaMA-CoS on the 8 BIG-bench tasks. LLaMA-CoS employs planning and calling of tools, which beats all CoT baselines by large margins and is on par with ChatGPT's CoS ability.

Baselines. As a comparison to CoS, we employ the chain-of-thought (CoT) reasoning as the baseline. We evaluate both methods under two scenarios: i) Prompting with demonstrations on Alpaca, LLaMA-7B, and ChatGPT, and ii) Finetuning specifically on the LLaMA-7B model. We referred to the LLaMA-7B tuned with CoT data as LLaMA-CoT, while our model, LLaMA-CoS, is specially tuned for tool use through CoS.

Results. We present the results in Table 4. Notably, LLaMA-CoS achieves an impressive average accuracy of 94.74%, outperforming all the CoT baselines, whether tuned or not, by a substantial margin. Compared to ChatGPT, which exhibits strong reasoning and tool-using capabilities under the CoS setting, our tuned model can still achieve comparable performance. These results highlight the effectiveness of CoS in outperforming traditional CoT methods and demonstrate the successful transfer of tool-using abilities from closed-source LLMs to smaller, open-source models.

4.3 Results Analysis

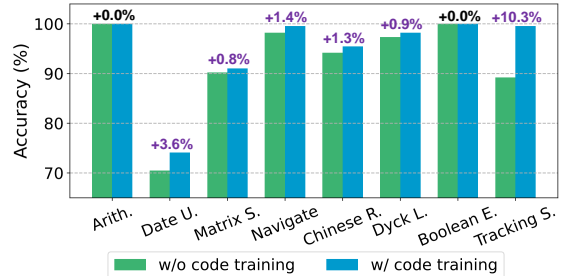**Excellence in Both Planning and Calling.** To comprehensively assess the CoS method, we sim-

Figure 3: The improvement of performance when code generation data points are involved during training.

ilarly report the individual contribution of CoS-Planning and CoS-Calling in Table 5. Our results demonstrate that CoS-Planning and CoS-Calling separately surpass the performance achieved by CoT-based models on all tasks. This validates the model's proficiency in both stages during CoS and underscores the rationale behind designing CoS-Planning and CoS-Calling to promote effective tool use under the Toolink framework.

Necessity of Code Training. To evaluate the impact of code generation data in CoS-GPT, we compare the LLaMA-7B tuned with or without them. The results in Figure 3 indicate that LLaMA-CoS

Method	Model	Arith.	Date U.	Matrix S.	Navigate	Chinese R.	Dyck L.	Boolean E.	Tracking S.
CoS-Whole	LLaMA-CoS	**100.00**	74.10	91.01	99.56	95.44	98.21	100.00	99.56
CoS-Planning	Alpaca	18.22	27.41	24.15	77.16	**100.00**	76.3	**97.59**	99.37
(*Prompting*	LLaMA-7B	74.11	27.71	25.02	77.16	**100.00**	93.80	**97.59**	**100.00**
w/ demo)	ChatGPT	**100.00**	66.16	**95.18**	94.78	**100.00**	74.58	95.39	99.85
CoS-Planning	LLaMA-CoS	**100.00**	**85.84**	89.62	**97.14**	**100.00**	**99.19**	**97.59**	**100.00**
CoS-Calling	Alpaca	99.44	24.70	30.08	48.60	17.97	1.56	89.91	6.78
(*Prompting*	LLaMA-7B	74.70	51.20	55.49	43.77	24.81	25.67	94.30	1.56
w/ demo)	ChatGPT	**100.00**	90.96	**97.44**	88.44	**95.67**	98.55	93.42	**100.00**
CoS-Calling	LLaMA-CoS	**100.00**	**91.57**	95.56	**98.88**	94.18	**98.55**	95.61	88.44

Table 5: The accuracy (%) of CoS-Planning and CoS-Calling separately on 8 BIG-bench tasks. Results show LLaMA-CoS has excellent ability in understanding and using tools through CoS.

Figure 4: Detailed error analysis of Alpaca and LLaMA-7B regarding CoS-Planning and CoS-Calling.

Task	If in CoS-GPT	CoS Stage	LLaMA-CoS	ChatGPT
AQUA-RAT	✓	*Planning*	**58.80**	52.90
		Calling	56.12	**65.94**
MATH	✓	*Planning*	**65.83**	52.61
		Calling	**50.75**	43.25
TabMWP	✓	*Planning*	**90.00**	60.75
		Calling	**66.00**	32.75
FinQA	✗	*Planning*	**70.51**	50.15
		Calling	22.38	**32.38**
GSM8K	✗	*Planning*	**61.29**	53.83
		Calling	**57.25**	36.50

Table 6: The accuracy (%) of CoS-Planning and CoS-Calling on five diverse datasets applying LLaMA-CoS or ChatGPT. Results show that LLaMA-CoS generally beats ChatGPT and is robust to unseen tasks.

trained with code generation data achieves higher accuracy, with an average improvement of 1.4%. This validates the necessity of training on code generation together with CoS ability. By incorporating these data points, the model learns to leverage codes as the medium for tool-using more effectively, which ultimately enhances task performance.

Error Analysis of LLaMA-7B and Alpaca. We discover from the results that the raw LLaMA-7B and Alpaca's performance lags far behind. To provide insights into why they fail to do CoS-Planning and CoS-Calling even with demonstrations, we conduct a detailed error analysis in fig. 4.

Upon analyzing the errors made by both models, we identified two primary tendencies: i) the models tend to learn the pattern but often overlook the utility of the tool and the purpose of the task; ii)

they frequently exhibit disarray in reasoning and a misalignment between the tool plan and the tool call. These issues contribute significantly to the subpar performance of both models.

Diverse Usage of Toolkit. Throughout the experiments, LLaMA-CoS exhibits diverse CoS-Calling patterns. It is capable of sequentially calling different tools to achieve a specific purpose, using tools in a non-linear logic (in a loop or with conditions), or performing nested tool calls, where the output from one tool directly serves as the other tool's input. These abilities illustrate the robustness and adaptability of LLaMA-CoS across diverse scenarios. We provide case studies and more details in Appendix G and Figure 5.

5 Further Studies

In this section, we show the generalization of LLaMA-CoS to novel tasks and how it can use

Seqencial Tool Calling: Multiply a matrix of shape (2,2,2) with a matrix of shape (2,2,1). Add the result to a matrix of shape (2,2,1). Compute the kronecker product of the result with a matrix of shape (2,4,3). Sum the result over the second axis.

Toolkit Creation

- multiply(shape, shape) ☑
- kronecker(shape, shape) ☑
- sum_over_axis(a, axis) ☑
- transpose(shape) ☐
- add_subtract_hadamard(shape1, shape2) ☑

CoS-Planning

First use **[multiply]** to calculate the shape of product.
Next use **[add_subtract_Hadamard]** to calculate the shape of sum.
Then use **[kronecker]** to calculate the shape of kronecker product.
Last we use **[sum_over_axis]** and pass axis=1 (first axis is 0, second is 1) to calculate the shape of the resulting matrix.

CoS-Calling

```
result = multiply([2,2,2], [2,2,1])
result = add_subtract_hadamard(result, [2,2,1])
result = kronecker(result, [2,4,3])
result = sum_over_axis(result, axis=1)
print(result)
```

(a) Sequential Tool Calling.

Conditional Tool Calling: You are asked to to predict the closing parentheses of a Dyck-n prefix. What's the closing parentheses for prefix: < ([< [ ] >] ([( )] ?

Toolkit Creation

- get_closing_parenthesis(opening) ☑
- get_opening_parenthesis(closing) ☐
- stack_insert(stack, element) ☑
- stack_pop(stack) ☑

CoS-Planning

If we encounter an opening parenthesis, we use **[stack_insert]** to insert the parenthesis into the stack.

If we encounter a closing parenthesis, we use **[stack_pop]** to remove the top element from the stack.

Finally, we use **[get_closing_parenthesis]** to get the closing parenthesis of the remaining elements in the stack.

CoS-Calling

```
expression = "< ( [ < [ ] > ] ( [ ( ) ]"
stack = []
for char in expression:
    if char in ['(', '[', '{', '<']:
        stack = stack_insert(stack, char)
    elif char in [')', ']', '}', '>']:
        stack = stack_pop(stack)
final = ""
for char in stack[::-1]:
    closing = get_closing_parenthesis(char)
    final += closing + " "
print(final)
```

(b) Conditional Tool Calling.

Nested Tool Calling: Jane visits the bookstore on the 16th of each month starting from the October of 2009. It is her 5th visit to the bookstore today. What is the date 24 hours later in MM/DD/YYYY?

Toolkit Creation

- add_time(start_day, years=0, months=0, days=0) ☑
- subtract_time(start_day, years=0, months=0, days=0) ☐
- convert_hour(hours) ☑

CoS-Planning

The starting day that she visits the bookstore is 10/16/2009. So I should use **[add_time]** to add 4 months to the October of 2009 to get the date today.
I am asked to calculate the date 24 hours later, so I should use **[convert_hour]** to convert 24 hours into days and use **[add_time]** to add the days to today's date and get the target date.

CoS-Calling

```
start = "10/16/2009"
# first calculate today's date, which is the fifth time
today_date = add_time(start, years=0, months=4, days=0)
# then calculate the date 24 hours later
target_date = add_time(today_date, years=0, months=0, days=convert_hour(24))
print(target_date)
```

(c) Nested Tool Calling.

Figure 5: Case Studies on the diverse CoS-Calling patterns in the main experiment.

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Task	Toolkit Origin	LLaMA-CoS	ChatGPT
Dynamic	*Raw*	97.50	80.83
Cnt.	*From Dyck L.*	73.30	79.17
Unit	*Raw*	70.83	80.83
Interp.	*From Arith.*	65.83	80.00

Table 7: The accuracy (%) of ChatGPT and LLaMA-CoS, with toolkit newly created for the target task (*Raw*) or borrowed from other tasks. Our results show that both ChatGPT and LLaMA-CoS can utilize tools not specifically tailored for the target task through CoS.

toolkits that are not specially tailored for solving the target task. These studies aim to illustrate the robustness of LLaMA-CoS in utilizing tools through planning and calling.

5.1 Generalization to Novel Tasks

The eight evaluation tasks (Srivastava et al., 2022) we previously used all have data points presented during training, despite only leveraging a few publicly available samples. To showcase the generalization ability of LLaMA-CoS, we further test it on two new tasks: FinQA (Chen et al., 2022b) and GSM8K (Cobbe et al., 2021). FinQA involves questions based on financial report data, while GSM8K involves grade school math problems.

Together with AQUA-RAT, MATH, and TabMWP, whose data are presented in CoS-GPT (as detailed in § 3.3), we randomly select a maximum of 400 test data points from each of the five tasks, ensuring they *do not* appear in CoS-GPT. We augment each data point with a toolkit, following the method outlined in § 3.3 regarding how CoS-GPT is constructed. In experiments, we follow the CoS-Planning and CoS-Calling tests outlined in § 4.1.

We show in Table 6 that LLaMA-CoS achieves high accuracy in both planning and calling stages and could even beat ChatGPT in performance. This affirms the effectiveness and robustness of its CoS ability even applied to unseen tasks. As our tests encompass math, finance, table reasoning, etc, this finding also emphasizes **the robustness of LLaMA-CoS across diverse types of tasks**.

5.2 CoS on Generic Toolkit

We further explore the ability of LLaMA-CoS to use a generic toolkit instead of the one specifically tailored for the target task. In real-world scenarios, toolkits are usually designed to address diverse tasks rather than tailored for a single task. We ex-

pect LLaMA-CoS and ChatGPT can apply toolkits borrowed from other tasks to solve the target query in a CoS approach.

To validate this, we source two additional tasks from BIG-bench: Dynamic Counting and Unit Interpretation. For each task, we provide a toolkit created explicitly for the target task or borrowed from another task. Specifically, we pair Dynamic Counting and Unit Interpretation respectively with Dyck Language and Arithmetic.

Under these settings, we evaluate the performance of both LLaMA-CoS and ChatGPT in Table 7 and show that **both LLaMA-CoS and Chat-GPT can utilize a generic toolkit borrowed from another task to solve target queries through CoS**. Though the performance still lags, these findings nevertheless confirm our assumption that CoS can increase the robustness of tool-using, and make our Toolink more applicable to real-world scenarios. We present more details in Appendix H.

6 Conclusions

We present Toolink, a tool-training framework that effectively applies toolkits to solve problems leveraging small, open-source language models. Toolink offers increased flexibility in adapting to diverse downstream tasks while addressing concerns related to high inference costs and privacy. Our main contributions include i) empirically implementing a framework that can effectively leverage open-source models' tool-using ability, ii) devising the chain-of-solving (CoS) method that links toolkit creation and tool use through robust planning and calling, and iii) releasing the CoS-GPT dataset that aims to enhance the model's CoS capabilities.

Specifically, our LLaMA-CoS model outperforms traditional CoT and achieves a comparable performance to ChatGPT concerning tool-using. We believe our study provides a solid foundation for future researchers to explore and enhance the tool-using capabilities of open-source models.

Limitations

Our experiments focus on equipping the open-source model with tool-using capabilities through the CoS approach, specifically in planning and calling, while excluding the ability to create toolkits. This limitation arises from the fact that the LLaMA-7B primarily relies on provided demonstrations and lacks the internal creativity required for toolkit cre-

ation. Moreover, the absence of enough training data further hampers the acquisition of this knowledge. We acknowledge this challenge posed by the transfer of the toolkit creation capability from closed-source models and leave it as an avenue for future research.

Additionally, it is important to note that though the tasks tested in our study include diverse toolkits and queries, they are mostly sourced from the BIG-bench dataset. To gain a more holistic understanding of the generalizability of our results, future research should expand the application of Toolink to a broader range of scenarios. This would enable a more comprehensive assessment of the framework's efficacy and applicability.

Ethics Statement

We consider the following issues in this paper:

- **Privacy** is a crucial aspect to consider when utilizing closed-source models such as ChatGPT and GPT4. These models have the potential to learn sensitive information internally, posing a risk to personal privacy. In contrast, Toolink addresses this concern by leveraging only a limited number of publicly available samples for toolkit creation, leaving the majority of testing queries blind to closed-source LLMs. This approach reduces the possibility of mishandling data and safeguards user privacy. By minimizing the exposure of sensitive information, Toolink mitigates the risks associated with privacy breaches when compared to closed-source models.

- **Transparency** is a key aspect that aims to enhance the interpretability and comprehensibility of AI systems from a human perspective. In Toolink, we prioritize transparency through the creation of toolkits that provide clear information about their utility, inputs, and outputs. Additionally, we disentangle the CoS into separate stages of planning and calling, which increases the interpretability of the model's reasoning for users. We also encourage future research to further document the specific scenarios in which our framework exhibits its maximum effectiveness, as well as to outline potential risks involved. This will contribute to a more comprehensive understanding of Toolink and facilitate informed decision-making.

- **Potential Bias** is another critical aspect that we prioritize addressing in our work. We acknowledge that bias and discrimination can inadver-

tently manifest through problematic examples present in the training data. To mitigate this concern, we adopt a meticulous approach to curate the CoS-GPT dataset, which consists of data points from various sources. We emphasize diversity to minimize the presence of potentially biased patterns during the data construction. Through these efforts, we aim to develop the model's tool-using and CoS ability that promotes equitable and unbiased outcomes, fostering trust and inclusiveness in the application of AI systems.

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Appendix

A Prompt Pattern for ChatGPT Toolkit

We show the pattern of the prompt we apply for the creation of toolkits leveraging GPT-3.5-turbo in Figure 6. The temperature is set to 0.3 to ensure the model clearly follows the instructions while retaining its creativity to a certain extent. The max length during generation is set to 1024. The prompt shown mainly consists of the instruction for toolkit creation, the demonstration of the format, sample public data, and the task description.

B Toolkits for tasks from BIG-bench

We show in Figures 8 to 15 the toolkits that GPT-3.5-turbo created leveraging the prompt mentioned in the previous section. Notice that we show the final version of the toolkit, which may contain certain modifications based on human feedback. For instance, in Figure 10, we have integrated addition, subtraction, and hadamard operation into one single tool, as all of them do not change the shape of the given matrix. This will effectively reduce the redundant tools and help the model learn with ease.

C Settings for Chain-of-Solving

C.1 Choice of Instruction

To inspire the models' ability to plan and call the tools during chain-of-solving (CoS), we apply clear instructions to prompt the model. For CoS-Planning, we choose the instruction "*You are presented with a question and several tools that may be useful. Select the useful tools and plan how to solve the problem.*", while for CoS-Calling, we choose the instruction "*Use the tool given in the input to write code to solve the problem.*". This applies to all the settings, including the LLaMA-CoS because it is also tuned in an instruction-following way.

C.2 Details about Demonstrations

For all the experiments leveraging ChatGPT, despite the instructions, we also provide the model with demonstration examples to showcase the format of planning and calling, as well as to better leverage its potential. The temperature is set to 0.3 during generation, and the max output length is set to 1024.

For the raw LLaMA-7B and Alpaca baselines without being tuned, the demonstration examples are also applied to provide guidance, while the LLaMA-CoS tuned under our Toolink framework does not need demonstration examples as it is already tuned under the instruction-following paradigm.

D Separated Test of CoS-Planning and CoS-Calling

In Toolink, planning and calling are combined as a whole CoS process, where the plans generated by the model are again fed back to itself to help guide the generation of the final tool calling decision. To disentangle their functions and better understand their role, we employ tests to measure their accuracy separately.

D.1 CoS-Planning Details

For the CoS-Planning test, we provide the model with the instructions and all the available tools in the toolkit. In Figure 7, we showcase the format of the CoS-Planning prompt given to the model.

However, plans are generated in the form of natural language, whose accuracy is hard to measure. For simplicity, we instead only measure if the correct tools are called upon to solve the given problem.

Suppose $K_T = \{k_1, k_2, ..., k_N\}$ is the toolkit with N tools for task T. For a specific query, we denote the set of useful tools as $K_{\mathsf{use}} \subseteq K_T$ and other redundant tools as $K_{\mathsf{rdt}} \subseteq K_T$. Suppose the set of tools called upon during planning is $K_{\mathsf{call}} \subseteq K_T$, then the correct tools called is denoted as $K_{\mathsf{correct}} = K_{\mathsf{call}} \cap K_{\mathsf{use}}$, and the erroneous tools called $K_{\mathsf{err}} = K_{\mathsf{call}} \cap K_{\mathsf{rdt}}$. These are the exact definitions of the variables that we apply in Equation (1).

If all the useful tools are called correctly and precisely, where $K_{\mathsf{call}} = T_{\mathsf{use}}$, the accuracy will be 1.00. Note that this metric is relatively strict because wrong calls will result in a reduction of accuracy.

D.2 CoS-Calling Details

For the CoS-Calling test, the standard (correct) plans will be provided to the model, instead of the plans that the model previously generated. The CoS-Calling test solely aims to investigate the model's ability to follow plans and generate the correct calling decisions. Besides the plans and instructions, only the useful tools with respect to the given query are provided in the prompt, instead

```
### Instruction:
You are asked to create a toolkit to solve the given task. Each tool in the toolkit should be a
Python function that is helpful to solve the problems in the task.
You will be given the related information about the task and the example queries to help you create
the useful tools.
For each tool you create, please first state the tool's name and its purpose, and then give its
implementation using python code. Please wrap the code in ```python … ```. You can create 2 to 5
tools for each task.

### Task 1
- Task Meta Information
The task asks the model to unscramble letters into a word. You should arrange the letters in correct
order and output a valid English word.
- Sample Queries
1. Q: Please unscramble the letters into a word, and write that word: imitedl  A: limited
2. Q: Please unscramble the letters into a word, and write that word: ermelonwat A: watermelon
3. Q: Please unscramble the letters into a word, and write that word: ttlebo   A: bottle
Please create a toolkit including Python functions that are useful in solving the problem.
### Response
- Tool 1:
permutations: this tool takes in a given string, generates all possible permutations of it, and
returns them in a list.
```python
import itertools
def permutations(word):
    perms = [''.join(p) for p in itertools.permutations(word)]
    return perms
```
- Tool 2:
valid_word_lookup: this tool takes in a string, checks whether it's a valid English word, and returns
a bool value.
```python
import nltk
from nltk.corpus import words
def valid_word_lookup(word):
    nltk.download('words')
    english_words = set(words.words())
    return word.lower() in english_words
```

Task 2
- Task Meta Information
[Meta Information of the Target Task]
- Sample Queries
[Sample Queries for Toolkit Generation in QA Format]
Please create a toolkit including Python functions that are useful in solving the problem.
Response
```

Figure 6: The pattern of the prompt given to GPT-3.5-turbo to generate the toolkit.

of all the tools from the toolkit. We showcase the format of the prompt given to the model in Figure 7.

The accuracy of CoS-Calling is based on the matching of the model's output to the correct answer. For tasks Arithmetic and Chinese Remainder, the accuracy is evaluated in numerical format; for Matrix Shape, the accuracy is evaluated based on the matching of dimensions list; for all other tasks from BIG-bench, the accuracy is based on the matching of strings between the model's output and the correct answer.

E   Dataset Construction

In this section, we provide more details about how CoS-GPT is constructed. We introduce respectively

the construction of tool-using data (including planning and calling) and code generation data. All the data points aim to enhance the open-source model's CoS ability.

E.1   Construction of Tool-Using Data

For each query in AQUA-RAT, GSM8K, and TabMWP, we first utilize ChatGPT to create a diverse set of tools that are potentially relevant to the given query, forming the toolkit. We then provide this toolkit to ChatGPT and allow it to select the most suitable tools. Subsequently, we prompt ChatGPT to generate decision calls based on the selected tools and manually verify the correctness of the resulting outputs. If the final answer is correct,

```
Prompt Format for Tool Plan:
### Instruction:
You are presented with a question and several tools that may be useful. Select the useful tools and
plan how to solve the problem.
### Input:
- Question:
[Query from data]
- Available Tools:
1. [Name: Introduction about purpose, inputs, outputs]
2. [Name: Introduction about purpose, inputs, outputs]
...
### Response:
```

```
Prompt Format for Tool Call:
### Instruction:
[Query from data]
Use the tool given in the input to write python code to solve the problem.
### Input:
- Tool 1:
[Name: Introduction about purpose, inputs, outputs]
[Simplified Code Realization]
- Tool 2:
[Name: Introduction about purpose, inputs, outputs]
[Simplified Code Realization]
...
- Plan
[Plan from Model's Tool Plan Response or the Standard (Correct) Plan]
### Response:
```

Figure 7: The format of the data (and prompt) for CoS-Planning and CoS-Calling.

we divide ChatGPT's responses into two distinct components, representing the planning stage and the calling stage, which are then individually added to the dataset. In this manner, the validity of our data points can thus be guaranteed.

Throughout these steps of data construction, we also incorporate demonstration examples sampled from the constructed dataset, thereby expanding the dataset in a self-iterative manner. Figure 7 shows detailed information about the format of the query. Besides the query, we also provide the corresponding CoS-Planning or CoS-Calling response and the implementation of the toolkit with useful and redundant tools.

E.2 Construction of Code Generation Data

The code generation data in CoS-GPT are sourced from 6 different venues, including Python-Simple, Python-Specific, Math, Algorithm, LeetCode, and Rectification. The objective behind these categories is to enhance the model's proficiency in problem-solving through code utilization, calling existing packages, applying reasoning, employing algorithms, completing codes of challenging competitions, and engaging in self-rectification.

For Python-Simple and Python-Specific, the former aims to boost the models' ability to solve simple problems using codes, while the latter aims to

enhance the model's ability to leverage code packages to solve more complex problems. Both these two sets are generated using ChatGPT. We prompt the model with instructions and demonstrations and gather the code snippets the model generated to solve the given problem.

The queries for the Math set are sampled from the training set of MathQA (Amini et al., 2019) and augmented with a code solution based on the given query and reasoning, leveraging ChatGPT. The generated programs are verified to ensure the output answer is the same as the correct one originally, thus ensuring the validity of the augmented data points. The Algorithm set is extracted from the open-source Python algorithm repository, with over 40 categories and more than a hundred diverse algorithms. For each algorithm, we ask ChatGPT to generate a query related to it and use a code snippet to solve the problem. The codes and corresponding queries are then gathered and formed into the instruction-following format.

For the LeetCode set, we directly extract the official open-sourced problems and the code answers from the website and form our data. The Rectification set is gathered from the error codes generated in the five sets before. The error tracebacks and the bad code snippet are fed into ChatGPT, and we leverage it to rectify the codes and generate a

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correct code snippet that can solve the given query successfully. We gather the generated codes and execute them again, retaining only the ones that give a correct answer finally and form the set based on these valid data points.

F Main Experiment Setting Details

For our main experiment, we finetuned the LLaMA-7B model on four A100-80G GPUs, with a total batch size of 32 and a learning rate of 1e-5. For the model whose performance we demonstrate in Table 4 and Table 5, its training dataset consists of 1.6K target task-specific data points (8 tasks, 100 for planning and 100 for calling each), 4K tool-using data and 3K code-generation data randomly sampled respectively from the CoS-GPT dataset. We trained the LLaMA-7B on these data for 3 epochs and obtained LLaMA-CoS.

In addition, for the ablation study about the training on codes we perform in § 4.3, we apply 7K tool-using data and remove all the code-generation data points. We keep all the other settings the same in this study.

G Case Studies of Diverse CoS Patterns

In Figure 5, we present three case studies highlighting the diverse nature of LLaMA-CoS in applying planning and calling for tool-using.

Firstly, LLaMA-CoS exhibits the ability to generate sequential plans involving different tools. In the first case, the model simulates the operation on matrices step by step in a linear way and finally gets the correct result.

Secondly, LLaMA-CoS demonstrates proficiency in executing complex tool calls within branch-loop structures. In the second case, the model learns to use different stack operations based on the character met in the expression, and can call the useful tool in a loop structure.

Lastly, the model showcases its competence in performing nested tool invocations. In the third case, the model is able to directly pass the converted hour retrieved from the previous tool as the input parameter for the next tool, which illustrates a successful nested tool call.

These examples serve to show the robustness, versatility, and adaptability of LLaMA-CoS across a wide range of scenarios.

H CoS on Generic Toolkit Details

We source two new tasks, Dynamic Counting and Unit Interpretation, from the BIG-bench. We apply all the problems in Dynamic Counting for our test of toolkit generalization. However, for Unit Interpretation, we specifically select the data from LV 1 in order for the tools from task Arithmetic to be properly applied. To ensure fairness, we expand the dataset by interactively sampling new questions with similar patterns from ChatGPT and incorporating them until the dataset reaches its original full size. Note that we only aim to showcase the toolkit's generalization ability and compare the performance of LLaMA-CoS and ChatGPT within this work, so we deem expanding the dataset as fair and reasonable under our settings.

We show the toolkits specially tailored for these two new tasks in Figures 16 and 17. The LLaMA-CoS model we apply is still the model we have trained in the main experiment, detailed in Appendix F. All the other settings, including the ChatGPT applied under our framework, are kept the same as that in the main experiment.

```
Toolkit for task: Arithmetic
- Tool 1:
add: it takes in two numbers and returns their sum
```python
def add(a, b):
    return a + b
```
- Tool 2:
sub: it takes in two numbers a and b and returns a - b
```python
def sub(a, b):
    return a - b
```
- Tool 3:
mul: it takes in two numbers and returns their product
```python
def mul(a, b):
    return a * b
```
- Tool 4:
div: it takes in two numbers a and b and returns the integer value of a / b
```python
def div(a, b):
    return int(a / b)
```
- Tool 5:
mod: it takes in two numbers a and b and returns a % b
```python
def mod(a, b):
    return a % b
```
```

Figure 8: The toolkit for task Arithmetic.

```
Toolkit for task: Date Understanding
- Tool 1:
add_time: It takes in the start day in format MM/DD/YYYY, and calculate the date after y years, m
months and d days. It returns a string in format MM/DD/YYYY.
```python
import datetime
def add_time(start_day, years=0, months=0, days=0):
    start_date = datetime.datetime.strptime(start_day, "%m/%d/%Y")
    new_date = start_date + datetime.timedelta(days=days)
    if new_date.month + months > 12:
        r = int((new_date.month + months) / 12)
        new_date = new_date.replace(year=new_date.year + years + r, month=(new_date.month + months -
            1) % 12 + 1)
    else:
        new_date = new_date.replace(year=new_date.year + years, month=new_date.month + months)
    return new_date.strftime("%m/%d/%Y")
```
- Tool 2:
subtract_time: It takes in the start day in format MM/DD/YYYY, and calculate the date y years, m
months and d days before this day. It returns a string in format MM/DD/YYYY.
```python
import datetime
def subtract_time(start_day, years=0, months=0, days=0):
    start_date = datetime.datetime.strptime(start_day, "%m/%d/%Y")
    new_date = start_date - datetime.timedelta(days=days)
    if new_date.month - months <= 0:
        r = int((new_date.month - months) / -12) + 1
        new_date = new_date.replace(year=new_date.year - years - r, month=(new_date.month - months -
            1) % 12 + 1)
    else:
        new_date = new_date.replace(year=new_date.year - years, month=new_date.month - months)
    return new_date.strftime("%m/%d/%Y")
```
- Tool 3:
convert_hour: It takes the number of hours and convert it into days (integer).
```python
import math
def convert_hour(hours):
    days = math.ceil(hours / 24)
    return days
```
```

Figure 9: The toolkit for task Date Understanding.

```python
Toolkit for task: Matrix Shape
- Tool 1:
multiply: it takes in two lists representing the shape of two matrix, and returns the shape of their
product.
```python
def multiply(shape1, shape2):
    if shape1[1] != shape2[0]:
        raise ValueError("Matrix shapes are not compatible for multiplication.")
    result_shape = shape1[:-1] + [shape2[-1]]
    return result_shape
```
- Tool 2:
kronecker: it takes in two list representing the shape of two matrix, and returns the shape of their
kronecker product.
```python
def kronecker(shape1, shape2):
    if len(shape1) != len(shape2):
        raise Exception("The number of dimensions of the two matrices is not equal")
    result_shape = [dim1 * dim2 for dim1, dim2 in zip(shape1, shape2)]
    return result_shape
```
- Tool 3:
sum_over_axis: it takes a list representing the shape of the matrix, and the dimension of the axis
that is to be sum up. It returns the shape of the resulting matrix.
```python
def sum_over_axis(shape, axis):
    if axis >= len(shape):
        raise ValueError("Invalid axis dimension.")

    result_shape = shape[:axis] + shape[axis+1:]
    return result_shape
```
- Tool 4:
transpose: it takes a list representing the shape of a matrix to be transposed, and returns the shape
of the resulting matrix.
```python
def transpose(shape):
    result_shape = list(reversed(shape))
    return result_shape
```
- Tool 5:
add_subtract_hadamard: it takes two lists representing the shape of two matrices for add, sbstract
and hadamard, and returns the shape of the resulting matrix.
```python
def add_subtract_hadamard(shape1, shape2):
    assert shape1 == shape2
    return shape1
```
```

Figure 10: The toolkit for task Matrix Shape.

```
Toolkit for task: Navigation
- Tool 1:
update_orientation: It takes the original orientation(N, E, S or W) and turn direction(left, right or
around), and returns the new orientation. It should be used only if not always face forward.
```python
def update_orientation(orientation, turn_direction):
    orientations = ["N", "E", "S", "W"]
    current_index = orientations.index(orientation)
    if turn_direction == "left":
        new_index = (current_index - 1) % 4
    elif turn_direction == "right":
        new_index = (current_index + 1) % 4
    elif turn_direction == "around":
        new_index = (current_index + 2) % 4
    else:
        raise ValueError("Invalid turn direction.")
    return orientations[new_index]
```
- Tool 2:
update_location: It takes the current location(x, y), orientation(N, E, S or W), and steps, and
returns the new location after action.
```python
def update_location(current_location, orientation, steps):
    x, y = current_location
    if orientation == "N":
        new_location = (x, y + steps)
    elif orientation == "E":
        new_location = (x + steps, y)
    elif orientation == "S":
        new_location = (x, y - steps)
    elif orientation == "W":
        new_location = (x - steps, y)
    return new_location
```
```

Figure 11: The toolkit for task Navigation.

```
Toolkit for task: Chinese Remainder
- Tool 1:
divide_remain: it takes in a, b, and c, and checks if the remainder of a divided by b is equal to c.
```python
def divide_remain(a, b, c):
    return a % b == c
```
- Tool 2:
check_validity: it takes into a list of possible answers, and filters the list of answers based on
the upper bound x.
```python
def check_validity(answers, x):
    return [answer for answer in answers if answer <= x]
```
```

Figure 12: The toolkit for task Chinese Remainder.

```
Toolkit for task: Dyck Language
- Tool 1:
get_closing_parenthesis: This tool takes in an opening parenthesis and returns the corresponding
closing parenthesis.
```python
def get_closing_parenthesis(opening):
    openings = ['(', '[', '{', '<']
    closings = [')', ']', '}', '>']
    if opening in openings:
        return closings[openings.index(opening)]
    else:
        return None
```

- Tool 2:
get_opening_parenthesis: This tool takes in an closing parenthesis and returns the corresponding
opening parenthesis.
```python
def get_opening_parenthesis(closing):
    openings = ['(', '[', '{', '<']
    closings = [')', ']', '}', '>']
    if closing in closings:
        return openings[closings.index(closing)]
    else:
        return None
```

- Tool 3:
stack_insert: This tool takes in a stack and an element and returns the stack with the element
inserted at the top.
```python
def stack_insert(stack, element):
    stack.append(element)
    return stack
```

- Tool 4:
stack_pop: This tool takes in a stack and returns the stack with the top element removed.
```python
def stack_pop(stack):
    if len(stack) > 0:
        stack.pop()
    return stack
```
```

Figure 13: The toolkit for task Dyck Language.

```
Toolkit for task: Boolean Expression
- Tool 1:
evaluate_expression: this tool takes in an expression as a string, evaluates it using Python's eval()
function, and returns the result.
```python
def evaluate_expression(expression):
    try:
        result = eval(expression)
        return result
    except SyntaxError:
        return "Invalid expression"
```

- Tool 2:
extract_valid_expressions: this tool takes in a string and extract the valid string that represents
the expression.
```python
def extract_valid_expressions(question_string):
    expression = question_string.split(':')[1].split('is')[0].strip()
    return expression
```
```

Figure 14: The toolkit for task Boolean Expression.

```
Toolkit for task: Tracking Shuffled Objects
- Tool 1:
create_object_dict: this tool takes in a list of people and their initial object, and returns a
dictionary mapping each person to their object.
```python
def create_object_dict(people, objects):
    object_dict = dict(zip(people, objects))
    return object_dict
```
- Tool 2:
update_object_dict: this tool takes in an object dictionary, a list of object trades, and updates the
object dictionary based on the trades.
```python
def update_object_dict(object_dict, trades):
    for trade in trades:
        person1, person2 = trade.split(' and ')
        object_dict[person1], object_dict[person2] = object_dict[person2], object_dict[person1]
    return object_dict
```
- Tool 3:
parse_trades: this tool takes in a string of trades and returns a list of individual trades.
```python
def update_object_dict(object_dict, trades):
    def parse_trades(trades_str):
    trades = trades_str.split('. Then, ')
    trades[0] = trades[0].replace('At the start', '')
    trades[-1] = trades[-1].replace('At the end', '')
    return trades
```
- Tool 4:
get_final_object: this tool takes in a object dictionary and returns the object held by the target
person finally.
```python
def get_final_object(object_dict, target_person):
    return object_dict[target_person]
```
```

Figure 15: The toolkit for task Tracking Shuffled Objects.

```
Toolkit for task: Dynamic Counting
- Tool 1:
get_closing_parenthesis: This tool takes in an opening parenthesis and returns the corresponding
closing parenthesis.
```python
def get_closing_parenthesis(opening):
    pairs_open = {'(': ')', '[': ']', '{': '}', '<': '>'}
    if opening in pairs_open:
        return pairs_open[opening]
    else:
        return None
```
- Tool 2:
find_open_remaining: This tool takes in a sequence of parenthesis and returns the single reamining
opening paraenthesis that is not closed.
```python
def find_open_remaining(parenthesis):
    parenthesis = parenthesis.split(" ")
    pairs_open = {'(': ')', '[': ']', '{': '}', '<': '>'}
    pairs_close = {')': '(', ']': '[', '}': '{', '>': '<'}
    stack = []
    for p in parenthesis:
        if p in pairs_open:
            stack.append(p)
        elif p in pairs_close:
            if pairs_close[p] in stack:
                stack.remove(pairs_close[p])
    return stack[0]
```
```

Figure 16: The toolkit for task Dynamic Counting.

```
Toolkit for task: Unit Interpretation (LV1)
- Tool 1:
same_ratio_calculate_first: This tool assumes that a : b = x : y. x is the first position. It takes
in a, b and y and returns x.
```python
def same_ratio_calculate_first(a, b, y):
    return (a / b) * y
```

- Tool 2:
same_ratio_calculate_second: This tool assumes that a : b = x : y. y is the second position. It takes
in a, b and x and returns y.
```python
def same_ratio_calculate_second(a, b, x):
    return (b / a) * x
```
```

Figure 17: The toolkit for task Unit Interpretation (LV 1).